

POPULATION-BASED ADVANCED OPTIMISATION ALGORITHMS FOR ELECTRICAL IMPEDANCE TOMOGRAPHY IMAGE RECONSTRUCTION

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Image Reconstruction**

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Certificate of Original Authorship

I, **TALHA ALI KHAN** declare that this thesis is submitted in fulfilment of the requirements for the award of *Doctor of Philosophy*, in the *School of Biomedical Engineering* at the *Faculty of Engineering & Information Technology* at the University of Technology Sydney.

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List of Symbols and Abbreviations

P_g	Global best position
v_i	Velocity of the particle
R	Random number [0-1]
D	Dimension of the search space
P_i	Local best position
x_i	Current position
χ	Constriction factor
w	Inertial weight
C_1, C_2	Two acceleration constants numbers
v_{max}	Maximum velocity of the particle
v_{min}	Minimum velocity of the particle
M_{pi}	Passive gravitational mass
$R_{ij}(t)$	Distance between two agents i and j
ε	Small constant
$G(t)$	Gravitational constant
M_{aj}	Active gravitational mass
K_{best}	Best agents having heavier masses
ρ	Charge density
E	Electric field
μ	Permeability
J	Current density
B	Magnetic field
$I(\vec{u})$	Electrical current
$\emptyset(\vec{u})$	Distribution of electrical potentials
Ω	Volume of interest also called as the domain
$\emptyset_{sur}(\vec{u})$	Distribution of electric potentials on surface electrodes
$\sigma(\vec{u})$	Distribution of electrical conductivities
$\partial\Omega$	Boundary of the domain

SPSO	Standard Particle Swarm Optimisation Algorithm
SGSA	Standard Gravitational Search Algorithm
APSO	Advanced Particle Swarm Optimisation Algorithm
AGSA	Advanced Gravitational Search Algorithm
HGSPSO	Hybrid Gravitational Search Particle Swarm Optimisation Algorithm
EIT	Electrical Impedance Tomography
FEM	Finite Element Method
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
EC	Evolutionary Computation
EAs	Evolutionary Algorithms
GA	Genetic Algorithm
SI	Swarm Intelligence
WOA	Whale Optimisation Algorithm
DE	Differential Evaluation
GAAPI	Hybrid Ant Colony Genetic Algorithm
ICS	Improved Cuckoo Search Algorithm
EIDORS Software	Electrical Impedance Tomography and Diffuse Optical Tomography Reconstruction Software

Thesis Publications

Published Journal Papers

- [1] **T. A. Khan**, and S. H. Ling, "A survey of the state-of-the-art swarm intelligence techniques and their application to an inverse design problem." *Journal of Computational Electronics*. <https://doi.org/10.1007/s10825-020-01567-6> (Published) (Impact factor: 1.532)
- [2] **T. A. Khan**, and S. H. Ling, "An improved gravitational search algorithm for solving an electromagnetic design problem." *Journal of Computational Electronics*, vol 19, issue 2, pp 773-339. (Published) (Impact factor: 1.532)
- [3] **T. A. Khan**, and S. H. Ling, "Review on Electrical Impedance Tomography: Artificial Intelligence Methods and its Applications." *Algorithms* 12, no. 5, pp.88. (Impact factor: 1.51)
- [4] **T. A. Khan**, S. H. Ling, and A. S. Mohan, "An Advanced Particle Swarm Optimizer with Novel Velocity and Position Update Strategies." *Information Sciences* (Accepted with revision). (Impact factor: 5.910)
- [5] **T. A. Khan**, and S. H. Ling, "A Novel Hybrid Gravitational Search Particle Swarm Optimization Algorithm." *Engineering Applications of Artificial Intelligence* (Accepted with revision). (Impact factor: 4.2)

Published Conference Papers

- [6] **T. A. Khan**, S. H. Ling, and A. S. Mohan, "Advanced Particle Swarm Optimization Algorithm with Improved Velocity Update Strategy," *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Miyazaki, Japan, 2018, pp. 3944-3949.
- [7] **T. A. Khan**, S. H. Ling, and A. S. Mohan, "Advanced Gravitational Search Algorithm with Modified Exploitation Strategy," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, 2019, pp. 1056-1061.

[8] **T. A. Khan**, S. H. Ling, N. Tram, and A. S. Mohan, "A Modified Particle Swarm Optimization Algorithm for Solving DNA Problem," *2019 60th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS)*, Riga, Latvia, 2019, pp. 1-5

Abstract

The necessity of preventing living tissues' direct exposure to ionising radiation has resulted in tremendous growth in the area of medical imaging and e-health, enhancing intensive care of perilous patients, and help to improve quality of life. Moreover, the practice of image-reconstruction instruments that utilise ionising radiation has a significant impact on the health of the patients. Long or frequent exposure to ionizing radiation is linked to several illnesses like Cancer. These factors urged to enhance the endeavours to advance non-invasive approaches, for instance, Electrical Impedance Tomography (EIT) which is a portable, non-invasive, low-cost, and safe imaging method. Nevertheless, EIT image reconstruction still demands more exploitation, as it is an inverse and ill-conditioned problem. Numerous numerical techniques are used to answer this problem without producing anatomically, unpredictable outcomes. Evolutionary Computational techniques can be used as substitutes to the conventional methods that usually create low-resolution blurry images.

EIT reconstruction techniques work on the principle of optimising the relative error of reconstruction utilising population-based optimisation methods that have been presented in this work. Three advanced optimisation methods have been developed to facilitate the iterative procedure for avoiding anatomically erratic solutions. Three different optimising techniques namely, a) Advanced Particle Swarm Optimisation Algorithm (APSO), b) Advanced Gravitational Search Algorithm (AGSA), and c) Hybrid Gravitational Search Particle Swarm Optimization Algorithm (HGSPSO) are used. By utilizing the advantages of these proposed techniques, the performance in terms of convergence and solution stability is improved.

The standard PSO (SPSO) algorithm tends to suffer from premature stagnation, gets trapped in the local minima, and loses exploration capability as the iteration progresses. To circumvent these problems, APSO is proposed, in which new strategies like velocity clamping and particle

penalization have been adopted. The new position and velocity update equations are presented in this work. Moreover, adaptive acceleration constants and inertial weight are used to maintain a balance between exploration and exploitation. The velocity clamping and particle penalization approach are used to bind the particle to explore within the search space (function domain) and avoid overshoot from the search space boundary. These modifications help the APSO algorithm to overcome the problems associated with SPSO.

Standard Gravitational Search Algorithm (SGSA) suffers from slow searching speed in the finishing stage due to the low exploitation capability. Therefore, to solve this problem and finding the middle ground between exploitation and exploration in the proposed method, the number of agents is decreasing over time. So that only the agents with the heavy masses can apply their forces on the neighbours, this approach needs to be used carefully; otherwise, it might weaken the exploration proficiency and enhance the exploitation ability. In the early stage, the algorithm must undergo a fast exploration phase to avoid trapping into a local optimum. As the iteration progresses, exploration must diminish, and exploitation must be focused. In AGSA, to facilitate the performance, only the K_{best} agents will attract the other agents. Similarly, further modification to facilitate the exploitation in AGSA is to make the step size smaller at the end of the iterations. A new term is added in the velocity update equation that will slow down the search process and help to find the optimum solution.

The third technique is based on the hybridization of the first two algorithms. The primary concept of HGSPSO is to integrate the capability of social thinking (*global best - gbest*) in APSO with the exploration ability of AGSA. A similar component to the social part in the velocity update equation of the standard PSO is introduced in the HGSPSO method. Since one of the drawbacks of the Standard GSA algorithm is that it does not have the memory to store the best solution, In HGSPSO, the best candidate solution is stored; hence it is available in every iteration and enhances exploration.

The three proposed algorithms were first tested on a range of standard benchmark functions. The functions include simple unimodal functions as well as complex multi-modal functions. The results from these functions are used to calibrate the control parameters of three algorithms, i.e. acceleration constants in APSO, gravitational constant in AGSA, and HGSPSO.

EIT images were obtained from the EIDORS library database for two case studies. The image reconstruction was optimized using the three proposed algorithms. EIDORS library was used for generating and solving forward and reverse problems. Two case studies were undertaken, i.e. circular tank simulation and gastric emptying. The results thus obtained are analysed and presented as a real-world application of population-based optimization methods.

Results obtained from the proposed methods are quantitatively assessed with ground truth images by using the relative mean squared error, confirming that a low error value is reached in the results. HGSPSO algorithm has superior performance as compared to the other proposed methods in terms of solution quality and stability.